# How to best support users in social learning platforms with recommendations?

Soude Fazeli, PhD candidate
Dr. Hendrik Drachsler
Prof. Dr. Peter Sloep

Centre for Learning Sciences and Technologies
celstec.org

## Open Discovery Space (ODS)

**A socially-powered, multilingual open learning infrastructure in Europe**


# Recommendations!

**Which recommender approach best fits ODS platform?**

**Limitations in learning domain:**

**Too sparse data**

**Too few 5-star ratings**

**No proper tags and annotations**

# Learning domain has its own data and limitations, expectations

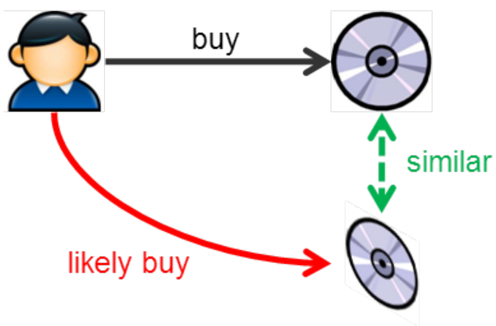
- Too sparse data
- Too few 5-star ratings
- No proper tags and annotations
- Can not use only popular reference datasets like MovieLens, Netflix, etc.

| Dataset | Users | Learning objects | Transactions | Sparsity (%) |
|---|---|---|---|---|
| MACE | 105 | 5,696 | 23,032 | 99.71 |
| OpenScout | 331 | 1,568 | 2,560 | 99.51 |
| MovieLens 100k | 941 | 1,512 | 96,719 | 93.69 |

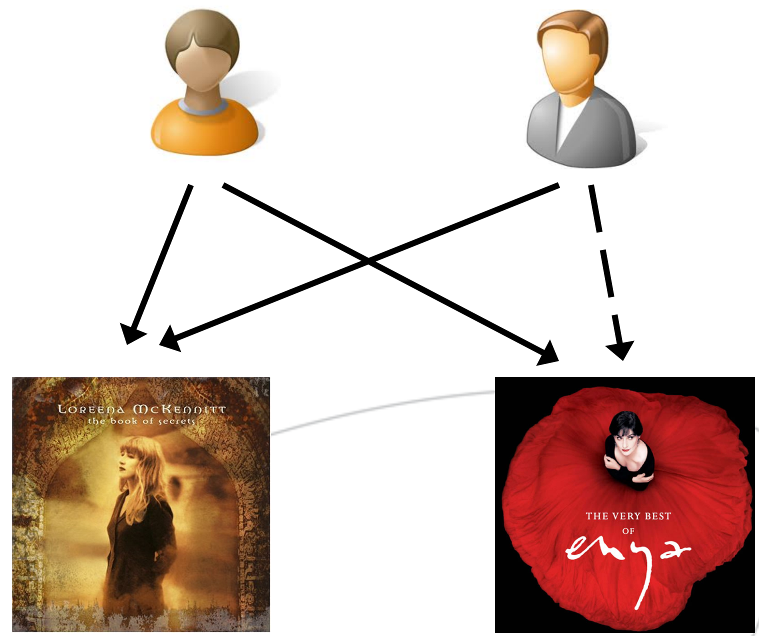

- *RQ:* How to best support users in social learning platforms with recommendations by using the data originating from social activities of users within the platform?
  - Performance metrics commonly used in recsys
  - Social network analysis
  - User satisfaction

# Recommender algorithms

1. Content-based




2. Collaborative filtering ✓



# Similarity

**Sparsity!**


Trustworthy users == like-minded users

Improving prediction accuracy of recommendations

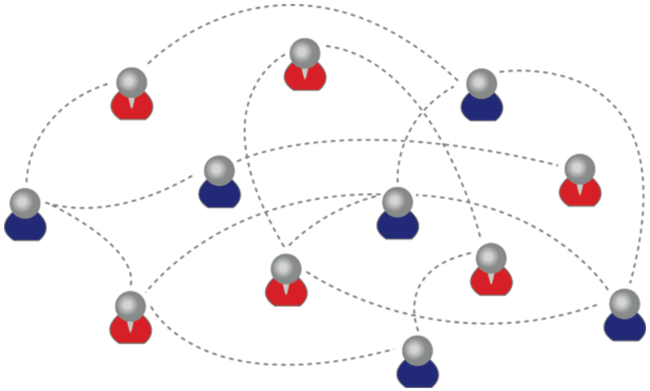
- Golbeck's TidalTrust
- Trust-aware recommender by Massa and Avesani
- Andersen et al's axiomatic approach
- T-BAR by Bellaachia and Alathel
- And many more…


All require users to give explicit trust ratings!

- Lathia et al.'s trust-based recommender #neal-lathia #recsys
- Trust model by O'Donovan and Smyth

# A social recommender system: T-index approach

## 1. Description

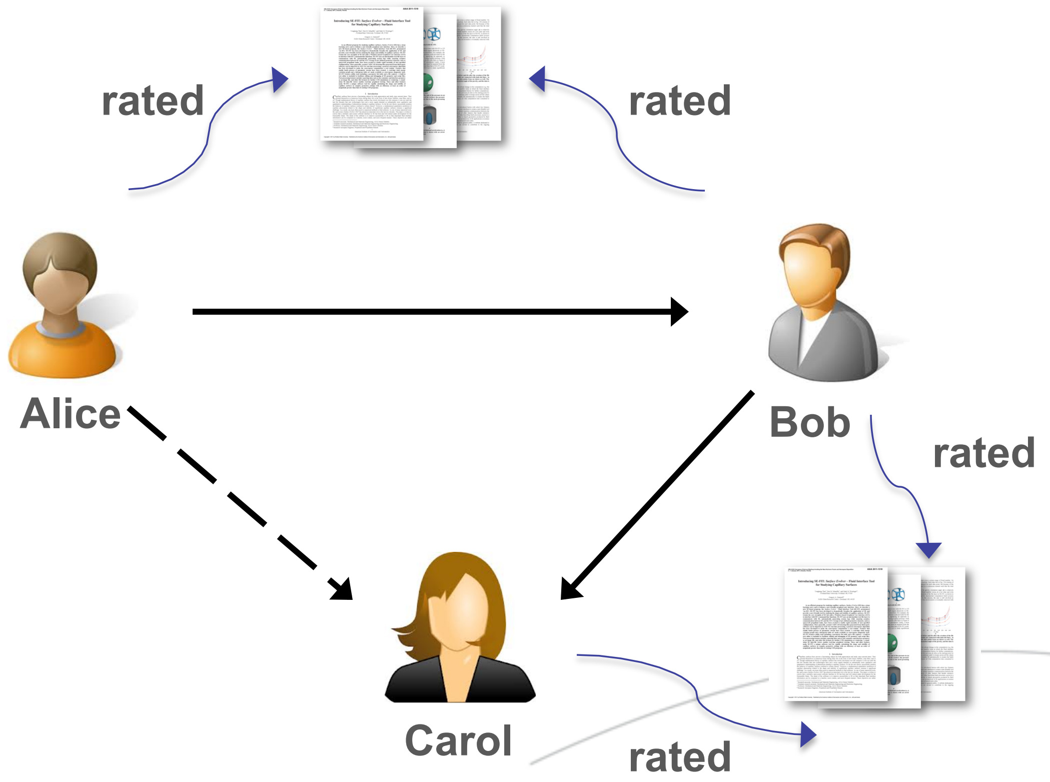


- Trust networks: a graph
  - Nodes: users
  - Edges: trust relationships
  - Weights: trust values originating from similarity
- Each user can be assumed as an agent
- Improve the process of finding nearest neighbors
  - T-index
  - TopTrustee

# A social recommender system: T-index approach

## 2. Trust propagation mechanism

- A new trust relationship between two far unconnected users is inferred if and only if:
  - Condition 1:
    - Mutual trust value between intermediate users is higher than a certain threshold (*v*)
  - Condition 2:
    - The number of connecting edges is lower than an upper bound (*L*)




**if A trusts B and B trusts C, then A trusts C if and only if condition 1 is met**
**and**
**condition 2 is met**

# A social recommender system: T-index approach

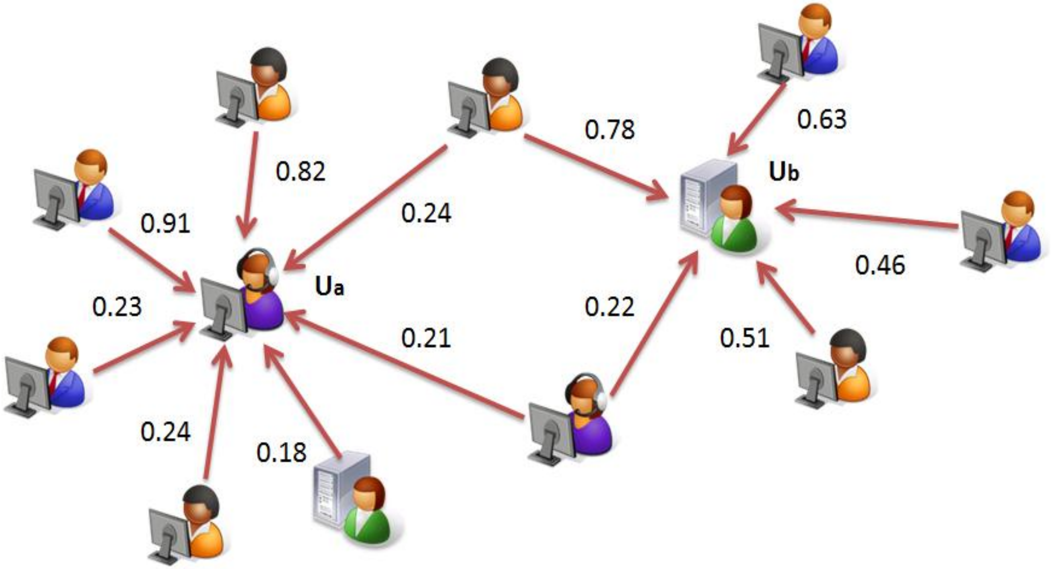
## 3. T-index?

*Note! Cluster*: a group of users who all trust a common user as the most trustworthy one (central user)

- T-index: measure of users' trustworthiness
- H-index: the impact of publications of an author

Indegree ($u_a$) = 7
Indegree ($u_b$) = 5

T-index ($u_a$) = 2
T-index ($u_b$) = 4



# A social recommender system: T-index approach

## 3. T-index?

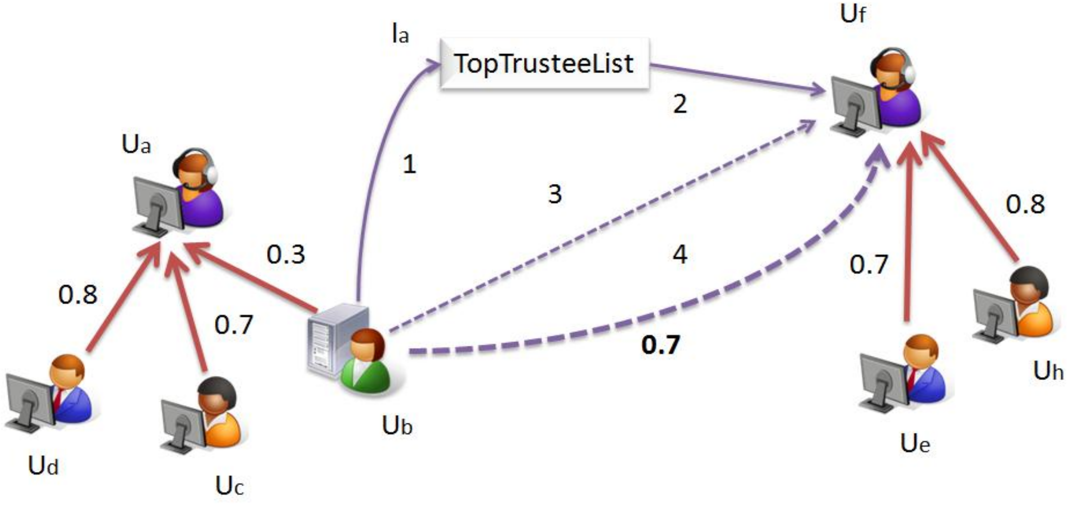
**Algorithm 1** Computing T-index

**procedure** COMPUTET-INDEX($user, TrusterList$)
  $TrusterValueList \leftarrow TrusterList$.sort($trustValue, desc$)
  **for all** $trustValue$ **in** $TrusterValueList$ **do**
    $trustValue \leftarrow$ multiply($trustValue, Max_{T-index}$)
  **end for**
  $Counter \leftarrow 1$
  **for all** $trustValue$ **in** $TrusterValueList$ **do**
    **if** $Counter < trustValue$ **then**
      $Counter \leftarrow Counter + 1$
    **else**
      **break**
    **end if**
  **end for**
  $T\text{-}index \leftarrow Counter - 1$
  **return** $T\text{-}index$
**end procedure**

# A social recommender system: T-index approach

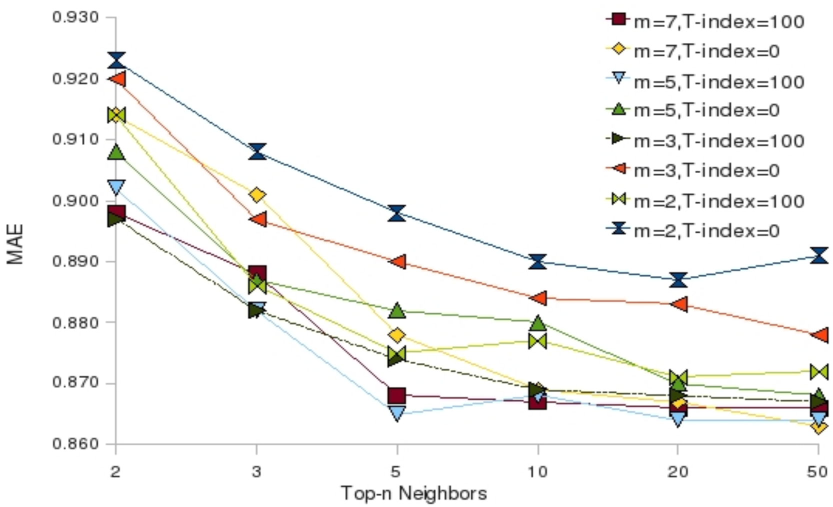
## 4. What T-index is for?

- TopTrustee : a list of top raters of an item sorted by T-index
- Helps the process of finding nearest neighbors
  - **Providing access to trustworthy users across the trust network including even those outside the traversal path length limit (L)**

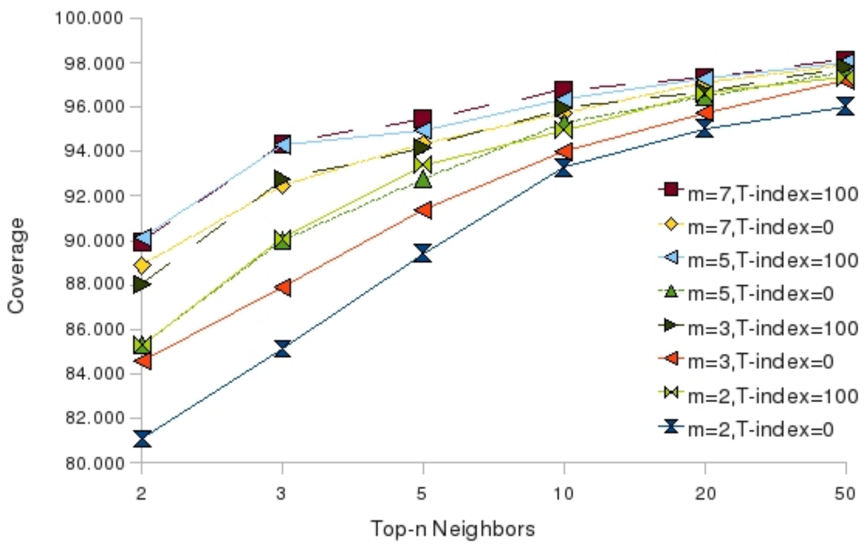


# A social recommender system: T-index approach

## 4. Results using MovieLens 100k




MAE with and without T-index




Coverage with and without T-index

# Data-driven study
## 1. Method

- Testing recommender algorithms
  - Trust-based recommender
    - If explicit trust is available (Epinion)
    - If not available: similarity measures + walking algorithm (modified BFS)
- Datasets
  - MovieLens 100k– reference dataset
  - MACE, OpenScout – quite similar to the future ODS dataset

# Data-driven study

## 3. Setting

- $v$ = 0.1 (Condition 1), $L$ = 3 (Condition 2)
- Training set 80% and test set 20%
- Sizes of neighborhoods $k$= (3,5,7,10,20)
- Size of TopTrustee list $m$=5

## Data-driven study
### 4. Tools

mahout

MySQL

Java

Gephi

# Data-driven study

## 5. Data

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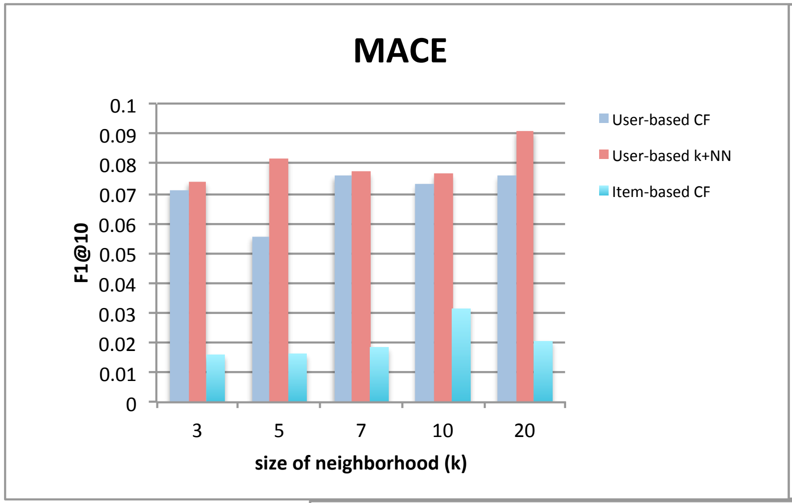
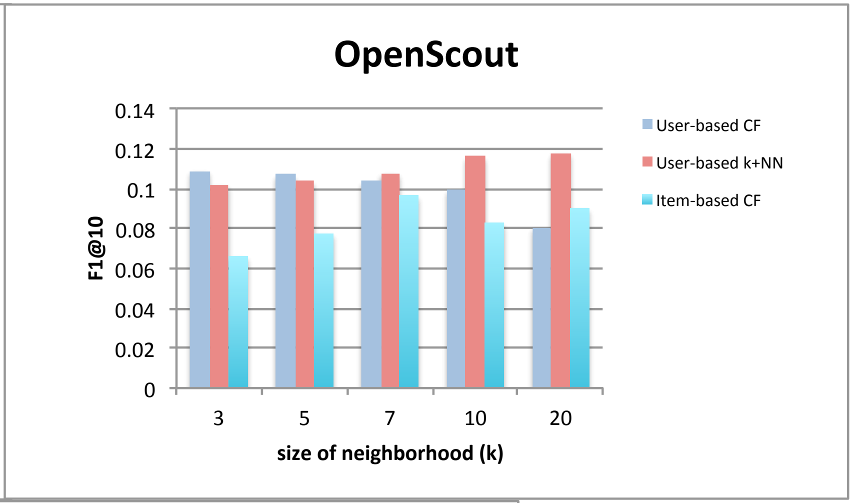
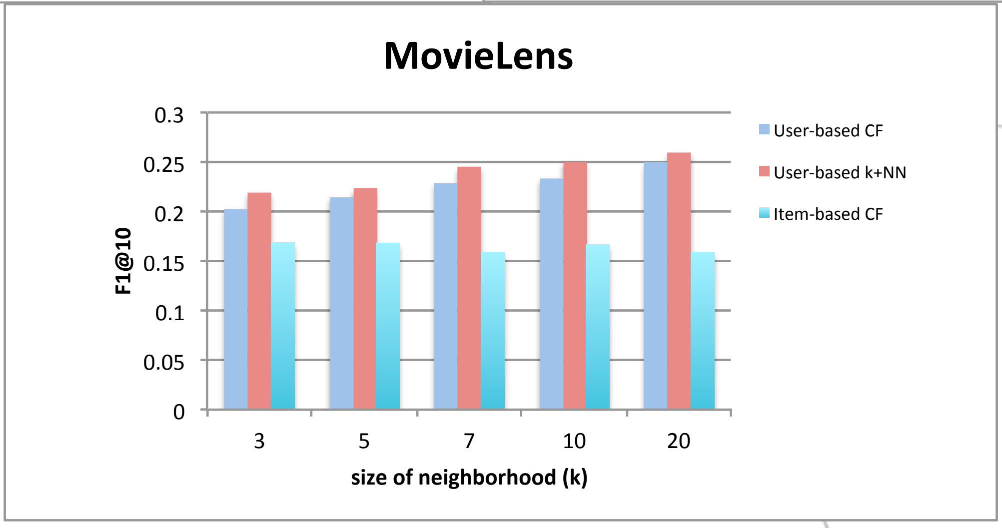
# Data-driven study

## 6. Results





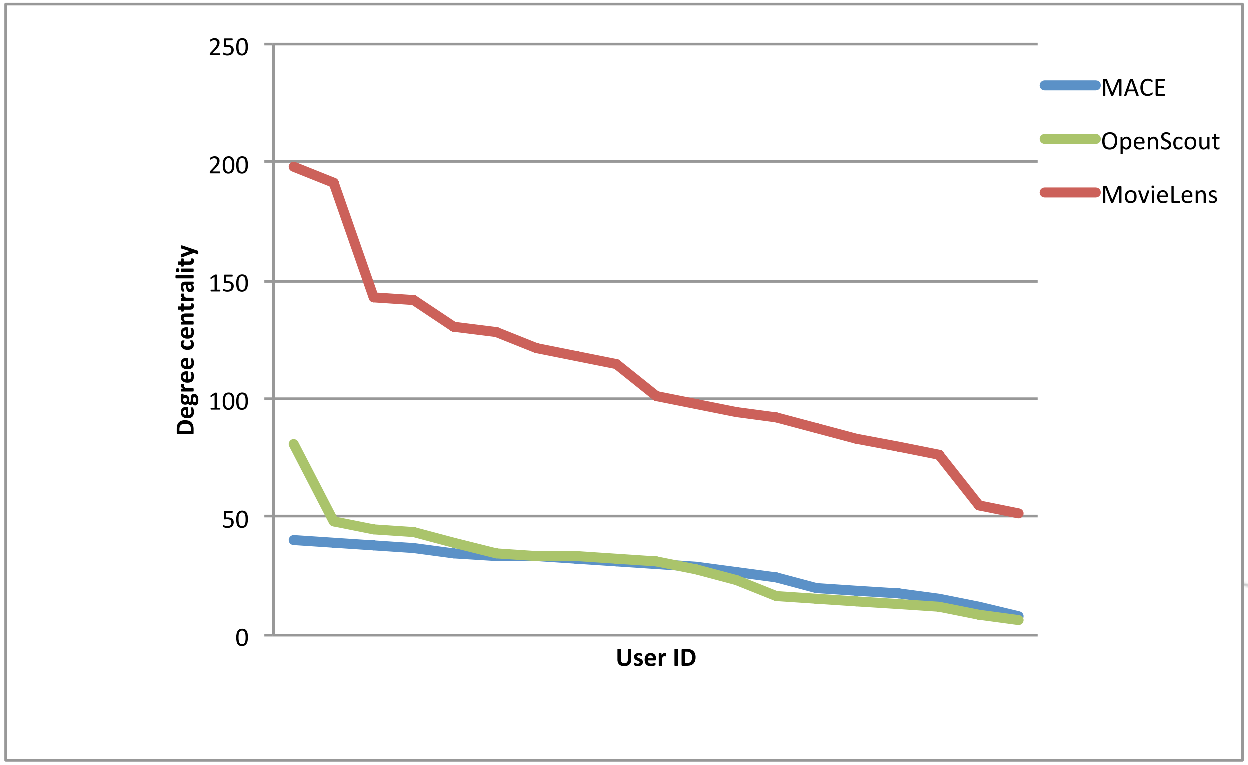

F1 of the K+NN and baseline CFs based on the size of neighborhoods

# Data-driven study

## 7. Implicit social networks for MovieLens

# Data-driven study

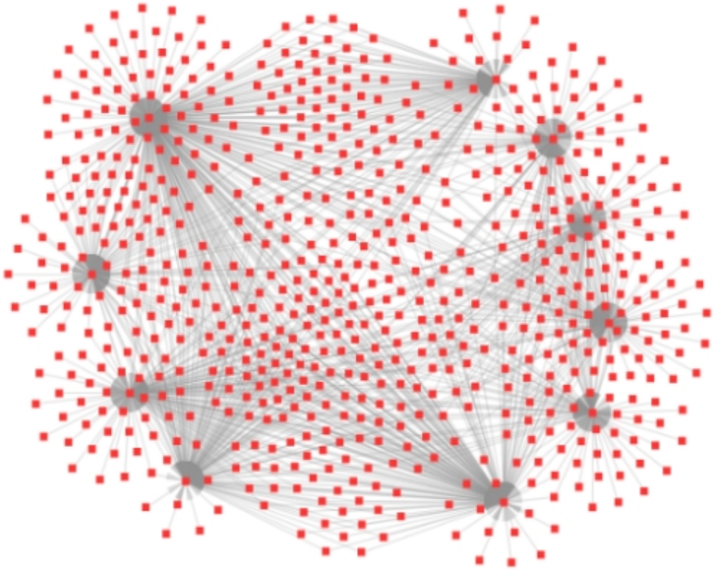
## 3. In-degree centrality



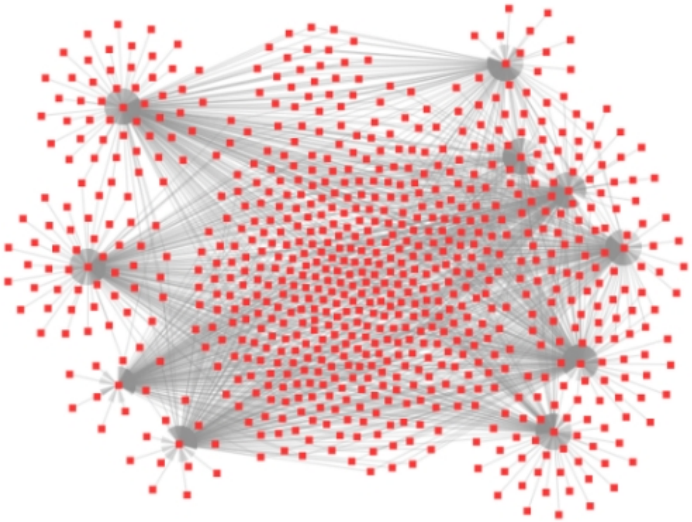

In-degree distribution of the users in the implicit social networks for different datasets using graph-based approach; k=10

# Data-driven study

## 4.2. Created trust network



**Without T-index**



**With T-index**

# Conclusion

- The aim is to support user in social platforms to find the novel and relevant recommendations on resources
- Trust-based recommender systems can be a solution

## Ongoing and Further work

- Go online with the ODS platform (October 2013)
- User evaluation study (December 2013)
- Evaluating trust-aware recommenders based on explicit trust ratings given by users: Massa et al., Golbeck, and T-index


**Soude Fazeli**
PhD candidate
Open University of the Netherlands
Centre for Learning Sciences and Technologies
(CELSTEC) PO-Box 2960
6401 DL Heerlen, The Netherlands
email: soude.fazeli@ou.nl

# Joint paper proposal

- Trust-based recommenders
  - Many of them are memory-based
  - A few studies on model-based
    - Using MF methods (Jamali et al., 2010)
      - Explicit trust e.g. Epinion
      - Evaluation only on common metrics: RMSE, Precision
    - MF + inferred trust
    - Explicit trust vs. inferred trust
    - Evaluation also in terms of SNA metrics
    - User satisfaction

- Hao Ma
    - Comparing implicit Trust-based recsys; explicit trust

- Diverse recommendations; not only similar ones
    - Initial recommendations
    - Filtering and refining recommendations using tree structures for item's content features
    - Aim: To make diverse recommendations